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An Ontology-based Method for Sparsity Problem in Tag Recommendation

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Abstract: Tags or personal metadata for annotating web resources have been widely adopted in Web 2.0 sites. However, as tags are freely chosen by users, the vocabularies are diverse, ambiguous and sometimes only meaningful to individuals. Tag recommenders may assist users during tagging process. Its objective is to suggest relevant tags to use as well as to help consolidating vocabulary in the systems. In this paper we discuss our approach for providing personalized tag recommendation by making use of existing domain ontology generated from folksonomy. Specifically we evaluated the approach in sparse situation. The evaluation shows that the proposed ontology-based method has improved the accuracy of tag recommendation in this situation.

1 INTRODUCTION

Tags or personally supplied keywords for describing web resources have been widely adopted in Web 2.0 sites. This facility can be found in social bookmarking such as Bibsonomy¹, multimedia sharing such as YouTube², e-commerce such as Amazon³ and more recently micro-blogs such as Twitter⁴ as well.

Tags are freely chosen words which act as annotation or metadata for describing web resources which can be used for personal organization, easy retrieval or finding related resources (Marlow et al., 2006). As users build up their tags collection, the aggregates of all users vocabulary may exhibit an informal taxonomy system which is known as folksonomy or folks taxonomy (Mathes, 2004).

However, since tags are chosen freely by users, tags vocabularies are diverse, potentially ambiguous and sometimes only meaningful to individuals. Besides variations in format such as plurality, pre- and suf-fixes), and case variations, these tags may also have polysemy (multiple meaning), synonymy and generality problems (Golder and Huberman, 2006) (Liang et al., 2010).

Tag recommender systems are a specialized recommender system for suggesting tags for annotating web resources. Specifically, a tag recommender system will recommend for a given user and a given item, a set of tags for annotating the item. Its objectives were to provide relevant tags and help consolidate the annotation vocabulary in the systems (Jäschke et al., 2008).

In this paper we present a tag recommender approach which aims to solve problems with ambiguities and generality during recommendation process. We utilize an existing domain ontology generated from folksonomy to represent tags as concepts with their relationships (Djuana et al., 2012). For a given user and a given item, by using the user-based collaborative filtering technique, a set of candidate tags can be produced. In this paper, we propose a method to expand the candidate tags by including more general or specific concepts based on the domain ontology. Moreover, we conduct experiments to evaluate performance of the proposed approach in sparse situation in which tag recommendation needs to be produced for users with less items, items with less tags and tags with less users.

This paper is structured as follows. We introduce some key concepts in Section 2. Then we present problem formulation and related works in Section 3. Section 4 discusses the adopted domain ontology as

¹<http://www.bibsonomy.org>

²<http://www.youtube.com>

³<http://www.amazon.com>

⁴<https://twitter.com/>

basis for recommendation framework. Section 5 discusses the proposed tag recommendation approach. Section 6 discusses evaluation and experiment results. And in Section 7 we conclude this paper and discuss some ideas for future work.

2 KEY CONCEPTS

In this section we introduce collaborative tagging system, tag recommendation, and ontology from folksonomy.

2.1 Collaborative Tagging Systems

A collaborative tagging system contains three entities: users, tags, and items, which are described below:

- Users $U = \{u_1, u_2, \dots, u_{|U|}\}$ contains all users in an online community who have used tags to organize their items.
- Tags $T = \{t_1, t_2, \dots, t_{|T|}\}$ contains all tags used by the users in U . Tags are typically arbitrary strings which could be a single word or short phrase. In this paper, a tag is defined as a sequence of terms. For $t \in T, t = \langle term_1, term_2, \dots, term_m \rangle$ A function is defined to return the terms in a tag: $tagset(t) = \{term_1, term_2, \dots, term_m\}$
- Items $I = \{i_1, i_2, \dots, i_{|I|}\}$ contains all domain-relevant items or resources. What is considered by an item depends on the type of user tagging collection, for instance, in Bibsonomy the items are mainly bookmarks and publications.

Based on these three entities, a collaborative tagging system is formulated as *Folksonomy* which consists of 4-tuple: $F = (U, T, I, Y)$ where U, T, I are finite sets, whose elements are the users, tags and items, respectively. Y is a ternary relation between them, i.e., $Y \subseteq U \times T \times I$, whose elements are called tag assignments or taggings. An element $(u, t, i) \in Y$ represents that user u collected item i using tag t . A function $Ft(u, i)$ is defined to return a set of tags that a user u has assigned to an item i whereby $Ft(u, i) = \{t \in T \mid (u, t, i) \in Y\}$ for all $u \in U$ and $i \in I$.

2.2 Tag Recommendation

A tag recommender system is a specific kind of recommender systems in which the goal is to recommend a set of tags to use for a particular item. Based on previous formulation of *Folksonomy*, the task of a tag recommender system is to recommend, for a given user $u \in U$ and a given item $i \in I$ which has not been

tagged by the user or $Ft(u, i) = \emptyset$, a set $\tilde{T}(u, i) \subseteq T$ of tags. In many cases $\tilde{T}(u, i) \subseteq T$ is computed by first generating a ranking on the set of tags according to some criterion, for instance by a collaborative filtering, content based, or other recommendation algorithms, from which then the top n tags are selected.

2.3 Ontology from Folksonomy

Ontology is formal description and explicit specification of a shared conceptualization (Gruber, 1993). Depending on the types of stored knowledge, ontology can be categorized in two types: domain ontology and general ontology (Navigli et al., 2003). General ontology defines concepts that are general for all domains. Domain ontology forms the core of any knowledge specifically for the domain.

Folksonomy which is emerging from collaborative tagging has been acknowledged as potential source for constructing ontology. As it captures vocabulary of users which may be aggregated to produce emergent semantics, people may develop lightweight ontologies (Mika, 2007).

3 MOTIVATION

In this section we discuss main motivation for this work by formulating main problem to solve and review related works for the proposed method and problem solution.

3.1 Problem Formulation

Sparsity problem (Adomavicius and Tuzhilin, 2005) refers to users who have rated very few items or items which have received very few ratings. In tag recommendation context, sparsity refers to users who tag a few or very few resources, and in some situation only one resource. It could also mean there are resources which received very few annotations and there are some tags which are only used by very few users.

Cold start (Schein et al., 2002) (Adomavicius and Tuzhilin, 2005) is a specific situation in recommender systems context when a new user arrives or new resource exists. In tag recommendation, each post consists of a user, a resource and all tags that this user has assigned to that resource. In this regards, cold-start problem may be formulated as (1) new user who posted for the first time in the system or in other words, all posts of a new user are in the test set or (2) new resource, on the other hand, refers to a resource that has never been tagged before by any other user (Preisach et al., 2010).

For these situations, most of the state of the art tag recommendation methods perform poorly (Preisach et al., 2010). In this paper we aim to present a tag recommendation method which may alleviate these problems by utilizing domain ontology generated from folksonomy.

3.2 Related Works

Tag recommender systems are broadly divided into three classes: content-based, collaborative filtering, and graph-based approaches (Musto et al., 2010).

One early content-based tag recommender is the work by (Brooks and Montanez, 2006). The state of the art works in this class include the approach by (Tatu et al., 2008) which mapped textual contents in Bibsonomy bookmarks, not just the tags, to concepts in WordNet and a similar approach by (Lipczak et al., 2009) which explored resource content as well as resource and user profiles. However, there is a drawback that these works relied on extended textual contents provided by Bibsonomy which are not always available in other collaborative tagging systems.

The baseline tag recommender system in collaborative class is the user-based CF (Marinho and Schmidt-Thieme, 2008). There is also a notable work by (Sigurbjörnsson and van Zwol, 2008) which is based on tag co-occurrences. Although this work has achieved good result, it didn't rely on actual meaning of tags which may miss the semantic relationships among tags.

The most notable works in graph-based approaches are the work by (Jäschke et al., 2008) which utilized a graph-based tag ranking method named FolkRank (Hotho et al., 2006) and the work by (Symeonidis et al., 2008) which proposed the Tensor Dimensionality Reduction method.

There wasn't much work done in using domain ontology for tag recommendation. Beside the work proposed in this paper there is a work by (Baruzzo et al., 2009) which used existing domain ontology to recommend new tags by analyzing textual content of a resource needed to be tagged. However, they didn't provide quantitative evaluation.

Most of the state of the art works in tag recommendation are evaluated on dense datasets and rarely on sparse datasets. The work we described in this paper is a tag recommender approach which combines collaborative filtering and graph-based method but not utilizing content-based methods. Although content-based methods may achieve good results for cold-start situation, they may not be applicable to all collaborative tagging systems because they rely on extra information on resources which are not always

available. It also may not be practical since for different content type they will need different version of the algorithm (Preisach et al., 2010).

4 ONTOLOGY SPECIFICATION

In this section we specify ontology specification which we are going to utilize in the tag recommendation approach proposed in this paper. Specifically this ontology specification discusses one particular approach that we have chosen for semantic and personalization capability of the generated domain ontology. Readers are referred to (Djuana et al., 2012) for more detailed discussion.

In order to use existing domain ontology generated from folksonomy, we specify the criteria in which the ontology has to conform to. This ontology of tags should come from a general ontology with good coverage. In particular this general ontology needs to have *synonym terms* (*synset*) or the like in their concept, and also general category or taxonomic grouping system such as WordNet (Fellbaum, 1998).

It was expected by conducting ontology learning process, domain ontology which represents a particular tag collection can be generated. There are 3 stages in domain ontology generation process which are: mapping tags to concepts, mapping disambiguation and relationships extraction.

It is possible that a tag can map directly to one of synonym terms of a concept in the backbone ontology. In other cases, only part of a tag that can map to one of synonym terms. These cases were handled by three mapping approaches which are (1) whole mapping (2) partial mapping and (3) term mapping.

After all possible mappings are found, the next stage was mapping disambiguation to choose the most appropriate concept from mapped concepts to represent the meaning of a tag for this particular tag collection. Two disambiguation strategies were performed which are (1) disambiguation by *frequency* which comes from an expert point of view about general meaning of tags. This mapping strength comes from frequency in a representative corpus of documents which indicate how frequent one particular synonym term would be used to represent the meaning of concept that contains these terms; (2) disambiguation by *tag relevance* which comes from users point of view about a personal meaning in tags collection. This mapping strength comes from tag relevance in relation to similar users understanding and usage of tags. Given a related tags that has been used for an item, this mapping is chosen according to relevance to other tags. After mapping disambiguation, each tag t

will map to one and only one concept. In the end, confirmed mappings according to two disambiguation strategies were: $M_{frequency}(t)$ and $M_{relevance}(t)$. Based on tag to concept mapping, available relationships ("is-a" relation) among concepts in general ontology were extracted to form domain ontology.

5 PROPOSED APPROACH

The proposed recommendation approach consists of two parts. The first part is the user-based collaborative filtering (CF) tag recommendation approach (user-based CF) (Jäschke et al., 2008) (Marinho and Schmidt-Thieme, 2008). This part will also serve as a baseline tag recommender for evaluation purpose. However, this approach may not be able to solve ambiguities problem since it can only recommend previously used tags and may not be able to recommend semantically related tags. Therefore, for the second part we proposed the ontology-based concept expansion tag recommendation approach. In this approach we utilize concepts and relationships which have been consolidated in the existing domain ontology. We attempt to improve the user-based CF by utilizing expanding vocabulary of recommended tags by making use of synonym terms and semantic relationships among related concepts in the ontology.

5.1 User-based CF Method

In the traditional user-based CF recommender systems for recommending items, user profiles are represented in a $|U| \times |I|$ user-item matrix X , where $|U|$ represents number of users and $|I|$ represents number of items. For each row vector: $\vec{x}_u = [x_{u,1}, \dots, x_{u,|I|}]$, for $u = 1, \dots, |U|$, $x_{u,i}$ indicates that user u rated item i by a rating value. Each row vector \vec{x}_u corresponds thus to a user profile representing the users preferences to the items.

Based on the profile matrix X , the neighbourhood of the most similar k users to the user u can be computed as follows:

$$N_u^k = \underset{v \in U}{\operatorname{argmax}} \operatorname{sim}(\vec{x}_u, \vec{x}_v) \quad (1)$$

where $\operatorname{sim}(\vec{x}_u, \vec{x}_v)$ is the similarity between user u and another user v . It can be calculated using a similarity calculation method such as cosine similarity.

However, because of the ternary relational nature of user tagging system, the traditional user-item matrix X cannot be applied directly in tag recommenders, unless the ternary relation Y is reduced to a lower dimensional space (Marinho and Schmidt-Thieme, 2008).

In order to apply the user-based CF, the ternary relation Y can be used to generate a $|U| \times |I|$ matrix $X_{UI} = [\vec{x}_1 \dots \vec{x}_{|I|}]$, called user-item(tag) matrix, with $\vec{x}_u = [x_{u,1}, \dots, x_{u,|I|}]$, for $u = 1, \dots, |U|$, $x_{u,i} \in \{0, 1\}$ indicating that, there exists tags used by user u to tag item i if $x_{u,i} = 1$, otherwise no tags have been used by user u to tag this item.

In the experiment, we implemented the user-item (tag) projection as the user profile matrix for calculating user neighbourhood. The user-item (tag) matrix is a binary matrix. Jaccards coefficient is used to measure the similarity of two binary vectors.

In this user-based CF method in order to recommend tags to a target user for tagging a particular item, it first generates a set of candidate tags which have been used by other users (usually neighbour users) to tag the item that target user is concerned. It then ranks the candidate tags based on the similarity between target user and other users to decide top n tags as the final recommendations.

Let $CT(u, i)$ be a set of tags which have been used by u 's neighbors to tag item i . $CT(u, i)$ are the candidate tags to be selected to generate recommendations to u for tagging i . For a candidate tag t in $CT(u, i)$, its ranking can be calculated by the following equation:

$$w(u, t, i) = \sum_{v \in N_u^k} \operatorname{sim}(\vec{x}_u, \vec{x}_v) * \delta(v, t, i),$$

$$\delta(v, t, i) = \begin{cases} 1 & (v, t, i) \in Y \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where $\delta(v, t, i) = 1$ indicates if the user v has used this tag t to tag the item i , N_u^k is the neighborhood of user u . The top n tags can be determined based on the ranking:

$$T(u, i) = \underset{t \in T}{\operatorname{argmax}}^n w(u, t, i) \quad (3)$$

5.2 Ontology-based Expansion Method

In this paper, we propose a method to improve the performance of the user-based CF (Jäschke et al., 2008) (Marinho and Schmidt-Thieme, 2008) described in Section 5.1 (also serves as baseline recommender).

In the proposed method, we generate candidate tags by utilizing the *synonym set* (*synset*) information captured in the tag ontology and rank candidate tags based on both user similarity and tag popularity. The recommendations generated by baseline recommender and tag ontology based recommender described in this Section are compared to evaluate the improvement achieved by the expansion method. The experiments and evaluation are provided in Section 6.

It is a well known insight to explore the possibility of using a more general or more specific tag in recommending a new vocabulary to user. It is related to

a characteristic known as the basic level variations or generality in collaborative tagging (Golder and Huberman, 2006) in which certain users tend to use a more general vocabulary while other users tend to use a more specific vocabulary.

Therefore in an expansion to current approach we introduce candidate tag expansion method which expands candidate tags to include the parent (more general) concept and the children (more specific) concepts as well as the basic level concepts. Each of these concepts will need to be ranked according to semantic relatedness measure to determine the closeness to current mapped concepts. These methods will be described below.

5.2.1 Candidate Tag Expansion

Let $CT(u, i)$ be the set of candidate tags generated based on neighbour users preferences. For each candidate tag t in $CT(u, i)$, by using the disambiguation mapping methods as described in Section 4, t can be mapped to concepts $M_{frequency}(t)$ or $M_{relevance}(t)$ in the tag ontology, respectively. For this step we will have 2 different sources of candidate tags as follows:

1. *Basic Level Tag Expansion* In this strategy, for mapped concepts which we identify as basic level expanded concepts, from the synset terms of these concepts, two expanded sets of candidate tags can be generated based on the two methods:

$$Exp_CT_{frequency}^{basic}(u, i) = \bigcup_{t \in CT(u, i)} synset(M_{frequency}(t)) \quad (4)$$

$$Exp_CT_{relevance}^{basic}(u, i) = \bigcup_{t \in CT(u, i)} synset(M_{relevance}(t)) \quad (5)$$

2. Parent-Children Level Tag Expansion

In this strategy, for parent and children concepts which we identify as more general and more specific concepts, we define two functions for retrieving those concepts. Let c be a concept, $parent(c)$ be the parent concept of c , and $children(c)$ be the set of children concepts of c . For a tag t , the set of its parent and children concepts are defined below:

$$PC_{frequency}(t) = \{parent(M_{frequency}(t))\} \cup children(M_{frequency}(t)) \quad (6)$$

$$PC_{relevance}(t) = \{parent(M_{relevance}(t))\} \cup children(M_{relevance}(t)) \quad (7)$$

From these parent and children concepts, another two expanded sets of candidate tags can also be generated:

$$Exp_CT_{frequency}^{PC}(u, i) = \bigcup_{t \in CT(u, i)} \bigcup_{c \in PC_{frequency}(t)} synset(M_{frequency}(t)) \quad (8)$$

$$Exp_CT_{relevance}^{PC}(u, i) = \bigcup_{t \in CT(u, i)} \bigcup_{c \in PC_{relevance}(t)} synset(M_{relevance}(t)) \quad (9)$$

5.2.2 Recommendation Ranking

For this step we will also have 2 different cases for ranking calculation as follows:

1. Basic Level Tag Expansion

For each of the candidate tag t in $CT(u, i)$, $Exp_CT_{frequency}^{basic}(u, i)$ or $Exp_CT_{relevance}^{basic}(u, i)$, its ranking is calculated by the following equation:

$$w_{\gamma}(u, t, i) = \begin{cases} \sum_{v \in N_u^k} sim(\vec{x}_u, \vec{x}_v) * \delta(v, t, i) & t \in CT(u, i) \\ \sum_{v \in N_u^k} sim(\vec{x}_u, \vec{x}_v) * \delta(v, t, i) * \mathcal{P}(t) & t \notin CT(u, i), \\ & t \in Exp_CT_{\gamma}^{basic}(u, i) \end{cases} \quad (10)$$

where $\gamma \in \{frequency, relevance\}$ and $\mathcal{P}(t)$ is the popularity of tag t , which is calculated as:

$$\mathcal{P}(t) = |UI_t| / \max_{t_i \in T} |UI_{t_i}|.$$

$\mathcal{P}(t)$ is the ratio between $|UI_t|$ and the maximum number of times that a tag has been used to tag items in this tagging community. As has been defined in (Djuana et al., 2012), $|UI_t|$ contains (user, item) pairs representing the tag assignments using tag t . $|UI_t|$ is the number of times that t has been used to tag items. The higher the $|UI_t|$, the more popular tag t is.

2. Parent-Children Level Tag Expansion

On the other hand for each t of candidate tags which are not original candidate tags in $CT(u, i)$ or the expanded basic tags in $Exp_CT_{\gamma}^{basic}(u, i)$,

t must be a parent or a child of a original candidate tag, i.e., $t \in \text{Exp_CT}_{frequency}^{PC}(u, i)$ or $t \in \text{Exp_CT}_{relevance}^{PC}(u, i)$. The ranking of tag t is calculated by the following equation:

$$w_\gamma(u, t, i) = \sum_{v \in N_u^k} \text{sim}(\vec{x}_u, \vec{x}_v) * \delta(v, t, i) * P(t) * S(t, t_o) \quad (11)$$

$t \notin CT(u, i), t \in \text{Exp_CT}_\gamma^{PC}(u, i)$

where $S(t, t_o)$ is the normalized similarity value between tag t and its original candidate tag based on WordNet similarity measures (semantic distance). In this approach we use Jiang-Conrath similarity measures which are based on information content in the glosses (Jiang and Conrath, 1997). We use the implementation in WordNet Similarity package (Pedersen et al., 2004). The more they closer in semantic distance, the higher the similarity value will be.

6 EVALUATION

In this section, first we discuss experiments setup then we present experiment results and discussion.

6.1 Experiments Setup

We have conducted experiments mainly using the dataset for ECML PKDD Discovery Challenge 2009 which is summarized in (Jäschke et al., 2012).

The dataset originated from Bibsonomy contains two versions of training data: (1) snapshot of almost all dumps of Bibsonomy and (2) dense part of the snapshot. The dense part contains training data which has been filtered to include only users, resources or tags that appear in at least two posts. This is also known as post core calculation (Batagelj and Zaveršnik, 2002) at level 2.

The dataset also contains two separate test data for (1) Content-based method whereby test data contained posts whose user, resource or tag were not contained in the dense part of training data and (2) Graph-based method otherwise. Table 1 and 2 summarized the statistics of the dataset.

We have simulated two situations in tag recommendation context which are tag recommendation using dense dataset and tag recommendation using sparse dataset.

For dense dataset we use the dense part of snapshot data in Table 1 for training data, and Graph based

Table 1: Training data statistics.

Statistics (until Dec. 31 st 2008)	Overall Snapshot	Dense part of Snapshot
#posts	421,928	64,120
#resources	378,378	22,389
#users	3,617	1,185
#tags	93,756	13,252

Table 2: Testing data statistics.

Statistics (Jan 1 st - June 30 th 2009)	Task 1 Content-based	Task 2 Graph-based
#posts	43,002	778
#resources	40,729	667
#users	1,591	136
#tags	34,051	862

data in Table 2 for testing data. In this simulation, all users, items and tags in test dataset are all contained in training data. For sparse dataset we use the entire snapshot data in Table 1 for training data, and Content based data in Table 2 for testing data. In this simulation, users, items or tags in test data were not contained in the dense part of training data which simulate sparse users and may contain cold start users or items.

Top N tags are recommended to each target user for one random user's items in testing set. The recommended tags are compared to target users actual tags of items in testing dataset. If a recommended tag matches with an actual tag, we calculate this as a hit. The standard precision and recall calculation are used to evaluate the accuracy of tag recommendations.

We have conducted following runs to compare performance between the baseline recommender and the proposed methods.

- *User-CF*: this is the user-based CF tag recommender system which is the baseline (section 5.1)
- *Exp_Freq_User_Syn*: this is the basic level *synset* expansion based on frequency over user-based CF (section 5.2)
- *Exp_Rel_User_Syn*: this is the basic level *synset* expansion based on tag relevance over user-based CF (section 5.2)
- *Freq&Rel_User_Syn*: this is the combination of *Exp_Freq_User_Syn* and *Exp_Rel_User_Syn*
- *Exp_Freq_User_PC*: this is the parent children *synset* expansion based on frequency over *Exp_Freq_User_Syn* (section 5.2)
- *Exp_Rel_User_PC*: this is the parent children *synset* expansion based on tag relevance over *Exp_Rel_User_Syn* (section 5.2)

- *Freq&Rel_User_PC*: this is the combination of *Exp_Freq_User_PC* and *Exp_Rel_User_PC*
- *Folkrank_TR*: this is the state of the art graph-based tag recommender (Jäschke et al., 2008).

6.2 Results and Discussion

For the recommendation using dense dataset the results are depicted in Table 3 and Table 4 while for the recommendation using sparse dataset the results are depicted in Table 5 and Table 6.

Table 3: Precision for Dense Recommendation.

N	5	10	15	20
<i>User-CF</i>	0.183	0.103	0.070	0.052
<i>Exp_Freq_User_Syn</i>	0.217	0.139	0.101	0.078
<i>Exp_Rel_User_Syn</i>	0.217	0.140	0.103	0.079
<i>Freq&Rel_User_Syn</i>	0.218	0.142	0.104	0.081
<i>Exp_Freq_User_PC</i>	0.221	0.144	0.103	0.079
<i>Exp_Rel_User_PC</i>	0.221	0.145	0.104	0.080
<i>Freq&Rel_User_PC</i>	0.222	0.147	0.104	0.081
<i>Folkrank_TR</i>	0.241	0.150	0.108	0.084

Table 4: Recall for Dense Recommendation.

N	5	10	15	20
<i>User-CF</i>	0.435	0.474	0.479	0.479
<i>Exp_Freq_User_Syn</i>	0.477	0.503	0.507	0.512
<i>Exp_Rel_User_Syn</i>	0.479	0.505	0.509	0.515
<i>Freq&Rel_User_Syn</i>	0.482	0.509	0.514	0.518
<i>Exp_Freq_User_PC</i>	0.515	0.562	0.574	0.587
<i>Exp_Rel_User_PC</i>	0.518	0.570	0.582	0.591
<i>Freq&Rel_User_PC</i>	0.523	0.578	0.588	0.593
<i>Folkrank_TR</i>	0.576	0.685	0.726	0.750

Table 5: Precision for Sparse Recommendation.

N	5	10	15	20
<i>User-CF</i>	0.074	0.059	0.053	0.051
<i>Exp_Freq_User_PC</i>	0.207	0.124	0.073	0.055
<i>Exp_Rel_User_PC</i>	0.207	0.125	0.075	0.056
<i>Freq&Rel_User_PC</i>	0.208	0.126	0.077	0.058
<i>Folkrank_TR</i>	0.205	0.121	0.066	0.051

For the recommendation using dense dataset we are mainly observing how expansion by basic level and parent-child synset expansion as well as combined method may improve significantly over the baseline recommender.

For the recommendation using sparse dataset we are mainly observing whether or not the proposed expansion methods can outperform the state of the art recommenders which are normally perform well in dense situation but not in sparse situation.

Table 6: Recall for Sparse Recommendation.

N	5	10	15	20
<i>User-CF</i>	0.169	0.238	0.302	0.340
<i>Exp_Freq_User_PC</i>	0.513	0.572	0.582	0.586
<i>Exp_Rel_User_PC</i>	0.514	0.574	0.583	0.588
<i>Freq&Rel_User_PC</i>	0.516	0.576	0.587	0.589
<i>Folkrank_TR</i>	0.491	0.561	0.574	0.585

The results of recommendation in dense dataset in Table 3 and Table 4 show that the basic level candidate tag expansion has improved the user-based CF quite significantly in precision and in recall while the parent-children expansion has improved further in precision and in recall over basic level expansion alone. Although these results are still lower than FolkRank results, the gap is getting closer for precision in higher number of N which shows potential of ontology based concept expansion for covering gaps in collaborative filtering methods.

As we predicted FolkRank didn't perform that well for sparse dataset as shown in Table 5 and Table 6. In this situation, the combination of all expansion methods has performed better than FolkRank in precision and in recall. If we look more closely at the results then the improvement to precision is more apparent for higher number of N while improvement to recall is more apparent for lower number of N. These results shows that proposed expansion method help avoid sudden decline in precision curve (maintaining accuracy) and help boost recall in first few recommended tag which are mostly more relevant tags.

Based on these results we may conclude that the proposed methods are quite effective for alleviating sparsity situation.

7 CONCLUSIONS

In this paper we have presented a tag recommendation approach which utilizes an existing domain ontology generated from Folksonomy for improving user-based CF method by expanding original candidate tags. We have presented an ontology-based expansion method which expands basic level tags and includes more general and more specific tags. We found that the expansion method based on basic level expansion improved the baseline method quite significantly. Specifically, in sparse and cold-start situations, the combination of all expansion methods has improved the accuracy even better than the state of the art graph based recommendation method which shows the potential of effectiveness in sparse situation.

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